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Chinese tourists in Nordic countries: An analysis of spatio-temporal behavior using geo-located travel blog data

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ARTICLE INFO

Keywords:

Chinese tourists
Spatio-temporal behavior
Nordic countries
Geo-located travel blog
Complex network

ABSTRACT

Geo-located travel blogs, a new data source, enable to achieve more detailed analysis of tourists' spatio-temporal behavior. Taking Chinese tourists in Nordic countries as the research object, this paper focuses on their behavior, seasonal patterns and complex network effects by using geo-located travel blog data collected from Qunar.com. The results show that: (1) Chinese tourists visiting Nordic countries are often experienced in traveling. The local climate during the cold season does not prevent them from pursuing the aurora scenery. (2) The travel behavior of Chinese tourists is spatially heterogeneous. The network analysis reveals that Iceland showcases stronger, compared to the other Nordic countries, community independence and small world effect. (3) During the warm season, Chinese tourists choose a variety of destinations, while in cold season, they tend to choose destinations with higher chances for spotting the northern lights. These results provide helpful information for the tourism management departments of Nordic countries to improve their marketing and development efforts directed for Chinese tourists.

1. Introduction

The behavior of tourists is a complex but purposeful process of human activity (Zillinger, 2007). Understanding the behavior of tourists is not only an interesting academic question but also an important basis for decisions concerning tourism management and development (Caldeira & Kastenholz, 2020). It is of great significance for the construction and development of tourism and transportation infrastructure as well as for the urban planning (Zhou, Xu, & Kimmons, 2015).

With the improvement of China's national economy and the relaxation of China's outbound tourism policy, the number of Chinese tourists is rising rapidly. Chinese tourists have become the key players in the global tourism market (Jin & Wang, 2016). Moreover, due to the uniqueness of Chinese culture, the behavior of Chinese tourists are often highly different from that of other international tourists (Liu, Huang, Bao, & Chen, 2019), thus showing a strong behavioral diversity in tourism destinations (Han, Kim, & Otoo, 2018). Therefore, Chinese tourists have become a typical object of research in the tourist behavior literature. Scholars have begun to focus on the behavior of Chinese tourists from several perspectives, such as response (Liu, Zhang, Zhang, Sun, & Qiu, 2019), cognition (Chen, Guevara Plaza, & Alarcón

Urbistondo, 2017; Liu, Huang, et al., 2019) and movement (Han et al., 2018; Zeng, 2018).

Nordic countries have always been a popular destination for Chinese tourists. With the implementation of the "Belt and Road Initiative", the relationship between China and Nordic countries is becoming increasingly close, thus, gradually forming a convenient "economic passage" (Zheng, 2019). The collaboration between these two "regions" have shown optimistic development trends; both in terms of trade cooperation and tourism. Under this background, the analysis of the behavior of Chinese tourists in Nordic countries is of great significance to further develop the tourism market, improve tourism services and enhance cultural exchange and cooperation between these two economic areas. However, except for some related works (Huijbens & Alessio, 2015; Larsen & Wolff, 2019) the contemporary academic literature has paid only a limited attention to Chinese tourists in Nordic countries. In fact, there is almost no relevant literature or detailed analysis of the spatio-temporal behavior of Chinese tourists in Nordic countries. Nordic countries, as a typical second-tier travel destination in Europe, commonly attract more mature and experienced Chinese tourists pursuing in-depth and special travel experiences (Jørgensen, Law, & King, 2018).

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<https://doi.org/10.1016/j.compenvurbysys.2020.101561>

Received 27 June 2020; Received in revised form 3 October 2020; Accepted 7 October 2020

Available online 13 October 2020

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Travel blogs have brought a new perspective to the detailed study of the behavior of Chinese tourists (Wu & Pearce, 2016). In recent years, travel sharing platforms have become increasingly popular in China. Thus, more and more Chinese tourists have started to write their own travel blogs and share them through the platforms. Especially with the rapid development of information and communication technology (ICT), China's online travel blogs have become an useful additional data source for geographical analysis on tourism, since they also include locational information. These "geo-located travel blogs", enable the analysis of the spatio-temporal behavior of Chinese tourists with higher precision than relying on traditional data sources such as statistical yearbooks.

In view of this, this paper provides a detailed analysis of the spatio-temporal behavior of Chinese tourists in Nordic countries by using geo-located travel blog data. By doing so, the paper is answering to the call voiced by Mou et al. (2020): the implicit information in the text data should be utilized in the geographic analysis of tourist flows to deepen the analysis of tourists' spatio-temporal behavior by uncovering the potential reasons behind seasonal variation of tourist flows and to incorporate textual data into the analysis to enrich it with descriptions on the drivers of tourist flows. The structure of this paper is as follows: the second section reviews the most relevant earlier literature on geo-located travel blogs and the behavior of Chinese tourists. The third section describes the research design (data and methods) applied in this paper. The fourth section introduces the results of the analysis. The fifth section discusses the main implications of the results. Finally, a concluding section summarizes the main takeaways of this paper in terms of the characteristics of spatio-temporal behavior of Chinese tourists in Nordic countries.

2. Literature review

2.1. Geo-located travel blog data in tourism

As travel blogs data originates from the voluntary sharing of information by tourists, these data can give a more detailed and comprehensive description of the behavior of tourists than the traditional data sources based on surveys and official statistics (Banyai, 2012; Chen et al., 2017). With the development of location-based services (LBS) in recent years, more and more social media platforms have integrated a LBS module into their blogging tools to enhance the reading experience of travel blogs by providing a new way for tourists to share their travel itinerary (Stock, 2018). These new type of travel blogs are termed as "geo-located travel blogs" (Kaufmann, Siegfried, Huck, & Stettler, 2019). Geo-located travel blogs, originating from the direct editing of tourists, include not only traditional text information, but also rich spatio-temporal label information, allowing a detailed description of tourists' journeys. Therefore, many scholars have started to pay increasing attention to geo-located travel blogs in recent years.

The research of "traditional" travel blogs has mainly focused on the semantic analysis of text, such as the image perception of destination (Leung, Law, & Lee, 2010) and the emotional information provided by the tourists (Shao, Chang, & Morrison, 2017). With the enhancement of the location characteristics of travel blog data, scholars have recently begun to use this locational information for analysing the spatio-temporal behavior of tourists. For instance, Manrique-Sancho, Avelar, Iturrioz-Aguirre, and Manso-Callejo (2018), Gao, Ye, Zhong, Wu, and Liu (2019) and Jin, Cheng, and Xu (2018) have studied, respectively, the spatial cognition and the patterns of mobility and temporal heterogeneity of tourists based on travel blog data. However, most scholars still use text extraction to obtain the location information of tourists in travel blogs. This approach is inevitably affected by the authors' writing styles. Thus, the obtained location information, calculated by geocoding, cannot accurately reflect the authors' real journeys. Using the location attributes of points of interest (POIs) set by the authors in geo-located travel blogs embedded in the LBS can solve this limitation.

2.2. Earlier analysis of tourists' spatio-temporal behavior

The analysis of tourists' spatio-temporal behavior is a popular research topic, but different scholars have varying research focuses. A common type of research is to classify tourists based on their temporal characteristics in order to compare their spatial behavior information. For instance, Vu, Li, Law, and Ye (2015) have compared tourists on the basis of 24-h activity time; Jin et al. (2018) have divided tourists into one-day trippers, two-day trippers and three or more day trippers; Walden-Schreiner, Rossi, Barros, Pickering, and Leung (2018) have compared tourists according to the month of their visiting date. Another common research stream is to analyze the temporal and spatial changes of tourists' behavior from the geospatial perspective. For instance, Li et al. (2011), Shao, Chang, and Morrison (2017) and Yang, Wu, Liu, and Kang (2017) have, respectively, utilized kernel density estimation, spatial clustering and exploratory spatial data techniques for these types of analysis. With the emergence of tourism data with strong locational characteristics (such as GPS tracking, geo-tagged photos, geo-located travel blogs, etc.), the second type of research has gradually become the "mainstream" of tourists' spatio-temporal behavior analysis.

At the same time, scholars have noticed that the diversified information on the movements of tourists produces complex network data (Baggio, Scott, & Cooper, 2010). Therefore, the theory of the "complex network" has gradually been introduced into the study of tourists' spatio-temporal behavior. For instance, Yang et al. (2017), Wu, Huang, Peng, Chen, and Liu (2018) and Mou et al. (2020) have utilized complex network theory to analyze the spatial-temporal behavior of tourists in such popular tourist destinations as Manhattan, Beijing and Shanghai. However, there are still many problems in the application of complex network theory to the analysis of tourists' spatio-temporal behavior. One of the main shortcomings relates to the application of community detection. For example, although Gao et al. (2019) and Qin, Song, Tang, Zhang, and Wang (2019) have detected communities in the tourist flow network of China, they have ignored the resolution limit of the community detection algorithm based on the complex network theory (Fortunato & Barthélemy, 2007).

Therefore, this paper, taking Chinese tourists in Nordic countries as the research object, focuses on the detailed analysis of the seasonal patterns and complex network effects of their travel behavior by using geo-located travel blog data and by applying the Annual Gini index, Pearson correlation coefficient and complex network theory.

3. Methodology

3.1. Study area

Nordic countries refer to the five sovereign countries of the Nordic Council, namely Denmark, Sweden, Norway, Finland and Iceland. Despite the cold climate, Nordic countries are renowned for their strong economy, rich welfare and attractive scenery. In 2018, the number of Chinese outbound tourists to Nordic countries exceeded 1 million. The outbreak of Covid-19 in 2020 has naturally affected these most recent numbers but the increase in the number of Chinese tourists has been striking (before the Covid-19 pandemic): their numbers grew from 2017 to 2018 by 212% in Sweden, 120% in Denmark and 77% in Finland.¹

3.2. Data collection and database construction

Qunar.com (<https://www.qunar.com/>), as China's leading travel search engine, is the largest Chinese online travel sharing website. The data from Qunar.com has been applied, for example, to the study of tourists' rating behavior (Zhang, Zhang, & Yang, 2016), tourist

¹ <https://baijiahao.baidu.com/s?id=1626676445495764621&wfr=spider&for=pc>

movement (Jin et al., 2018; Mou, Zheng, et al., 2020) and destination image (Lian & Yu, 2017). The website provides an intelligent editing scheme for travel blogs: when writing blogs on the website, tourists can set up spatio-temporal labels (recorded in the source code of the blog's webpage) of the attractions involved in the blog. Moreover, the LBS platform of the website helps to generate visual travel routes. We selected 599 travel blogs, voluntarily shared by Chinese tourists visiting Nordic countries, from 2012 to 2019 as our initial data.

Due to the complexity of the underlying data structure of the travel blogs in Qunar.com, it was necessary to design webpage recognition rules for standardized information extraction. As an automated process, the main principle of this design is to browse the publicly available webpages through programming simulation and store the visible information in a structured way. The data structure of travel blogs in Qunar.com and the information extraction-storage scheme are shown in Fig. 1.

As shown in Fig. 1, the travel blogs in Qunar.com adopt a hierarchical data organization mode, that is, the blogs are made of multiple experiences with multiple POIs. In order to provide a more intuitive display of the behavior characteristics of tourists, we divided the travel blog data extracted from Qunar.com into two parts, namely, "trajectory data" (the spatial distribution is shown in Fig. 2) and "cognitive data" (experiences and perceptions), and stored them in two separate databases. The POI sequence is used to record the movement of tourists between attractions in the trajectory database, while the cognition database stores the blog text describing the tourists' travel experience. In addition, due to the high likelihood of information errors and logic problems, we designed rules to clean the travel blog data before storing it into the databases. These rules include: (1) removing travel blogs without spatio-temporal labels; (2) removing experience records if they relate to places outside the five Nordic countries; and (3) removing duplicate attraction data (if the POI number of the same attraction appears sequentially in the data, it was deemed that the user has not moved from the attraction, and the redundant records, therefore, deleted). After applying these data cleaning rules, we ended up with 490 geo-located travel blogs containing information on 358 individual attractions (nodes) in Nordic countries, 5386 visits to these attractions and 1540 edges between them.

Fig. 3 shows a descriptive analysis of the data. As shown in Fig. 3(a), in our data, Norway is the most and Denmark the least popular Nordic country for Chinese tourists. This result is consistent with official statistical data on Chinese tourism (UNWTO, 2020). As shown in Fig. 3(b), The Oslo City Hall in Norway is the most frequently visited individual

attractions in the data, followed by Gamla Stan in Sweden, The Little Mermaid in Denmark and Stockholms Stadshus in Sweden.

3.3. Analysis of tourists' spatio-temporal behavior

3.3.1. Analysis of temporal behavior

The analysis of temporal patterns and change is an integral part of tourist behavior research. In this paper, we focus on the seasonal variation of tourists' travel behavior, reflected in geo-located travel blog data, and selected two indicators, namely the Annual Gini index and Pearson correlation coefficient, to analyze the temporal behavior of Chinese tourists in Nordic countries.

(1) Annual Gini index

Annual Gini index can be used to measure the seasonal concentration of the variables in tourism research (Fernández-Morales, 2003). It is calculated as follows:

$$G = \frac{1}{2} \cdot \frac{\sum_{i=1}^n \sum_{j=1}^n \frac{|X_i - X_j|}{n^2}}{\bar{X}}, \quad G \in \left(0, 1 - \frac{1}{n}\right) \quad (1)$$

Where, G is the Annual Gini index; X_i and X_j are the numbers of tourists' in the i th or j th study period; \bar{X} is the average number of tourists' for all the study periods; n is the total number of study periods (in our case months; i.e. 12). High values ($G > 0.4$) mean that the tourist distribution is concentrated on certain months, while low values ($G < 0.3$) indicate that the tourist distribution is evenly spread across the year.

(2) Pearson correlation coefficient

Pearson correlation coefficient can be used to measure the linear correlation between two variables. The two variables need to conform to normal distribution, which can be proved by K-S test. The value of Pearson correlation coefficient is between -1 and 1 . When the value is 1 , it means that there is a perfect positive correlation between the two variables; when the value is -1 , it means that there is a perfect negative correlation between the two variables; when the value is 0 , it means that there is no linear correlation between the two variables. The significance of the results is verified with the two-tailed " p -value" test. Generally, p -values < 0.05 are deemed as statistically significant.

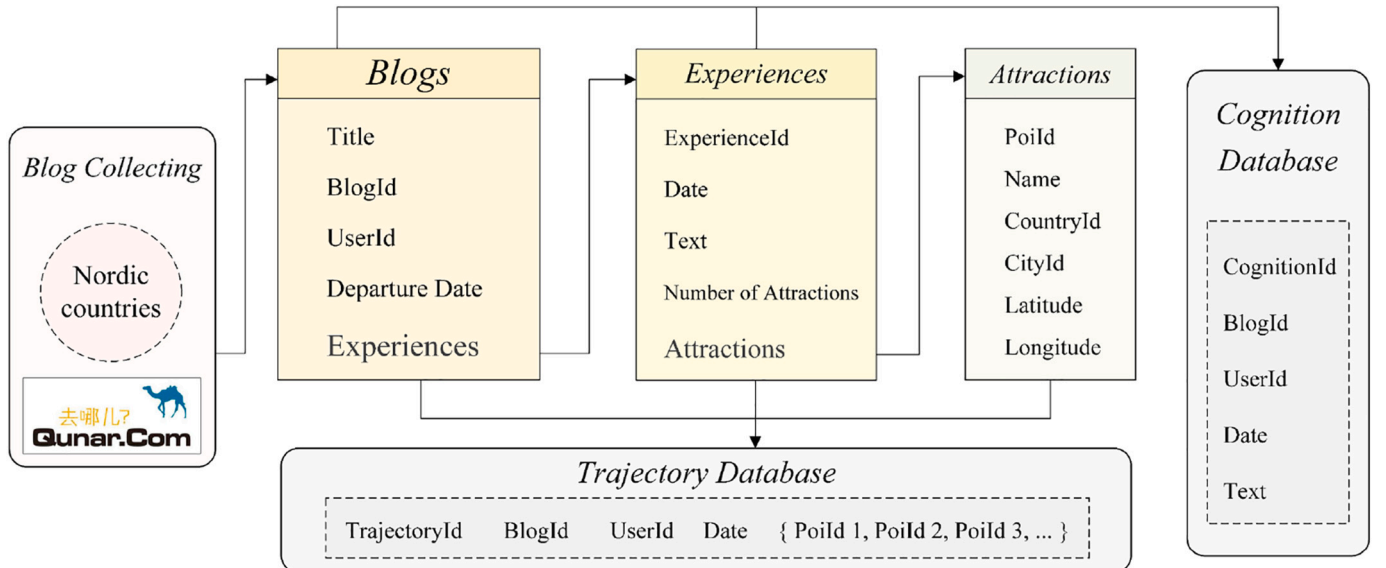


Fig. 1. The data structure of the geo-located travel blogs in Qunar.com and our information extraction-storage scheme.

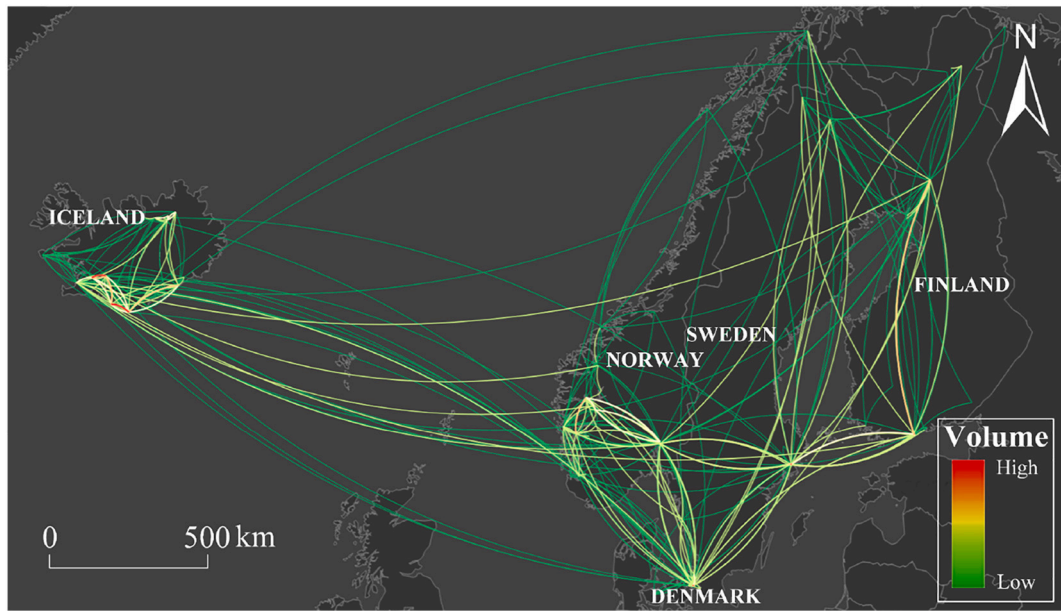
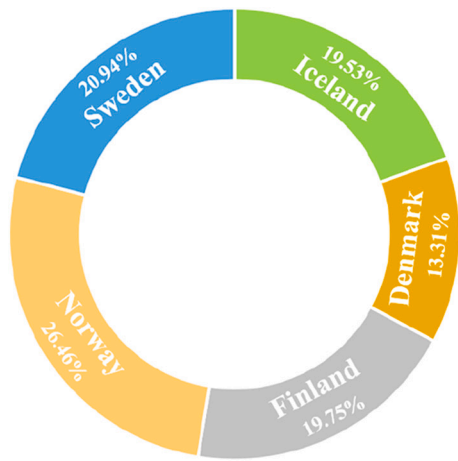
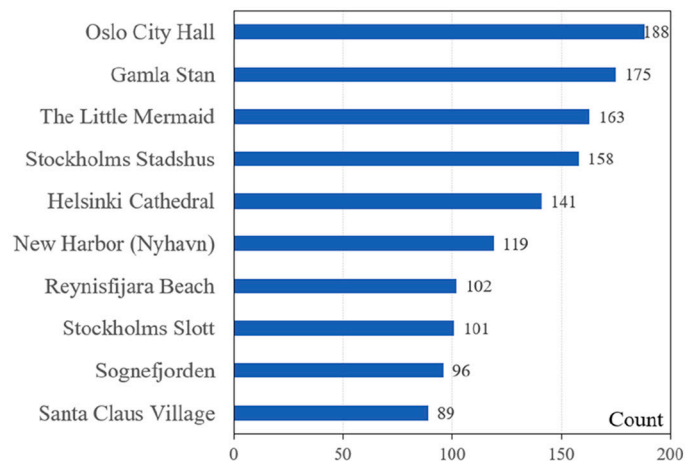


Fig. 2. The spatial distribution of the travel trajectories of Chinese tourists in Nordic countries.



(a) Countries visited



(b) Popular attractions visited

Fig. 3. Descriptive analysis of geo-located travel blog data in Nordic countries.

3.3.2. Analysis of spatial behavior

Complex networks can abstractly describe the movement of tourists between destinations, allowing researchers to gain a deeper understanding of the spatial patterns of tourist flows. Thus, the complex network theory was introduced into the tourism literature to provide new perspectives for tourists' spatial behavior analysis. In our complex network, attractions were abstracted as nodes and the tourist flows between attractions as edges with weights. The weights are based on the number of movements of tourist between two attractions in the data. We utilized structure evaluation and community detection to explore the network effects of tourists' spatial behavior.

(1) Network structure evaluation.

Six metrics, including node degree, weighted degree, betweenness centrality, average shortest path length, average clustering coefficient and gravity center, were selected to evaluate the structural characteristics of the tourist flow network of Chinese tourists in Nordic countries

(Table 1).

(2) Community detection.

In the complex network theory, community refers to a dense sub-network within a larger network (Newman, 2012). That is, to a group of nodes that have more dense ties within the group than to nodes outside the group (Luthe & Wyss, 2016). Community detection provides a classical method for understanding the spatial structure of complex networks in geographical space (Ye, She, & Benya, 2018; Zhong, Arisona, Huang, Batty, & Schmitt, 2014). For tourism research, it is a data-driven method of extracting tourism districts (Shao, Zhang, & Li, 2017), which can be used in comparison with official administrative divisions.

Among many community detection methods, algorithms based on "modularity" have been shown to have high performance (Lancichinetti & Fortunato, 2009). In short, modularity is a metric to measure the strength of the community structure of a complex network. It is defined as follows:

Table 1

The applied metrics of network structure evaluation.

Name	Definition	Formula
Node degree	Reflects the importance of nodes in the network.	$d_i = \sum_{j=1}^n L_{ij} \quad (2)$ <p>Where, L_{ij} is the number of edges between node v_i and node v_j; n is the total number of nodes.</p>
Weighted degree	Reflects the connection frequency between the target node and the adjacent node in the network, further divided into weighted in-degree and weighted out-degree.	$S_{i,out} = \sum_{j \in N_i} w_{ij}, S_{i,in} = \sum_{j \in N_i} w_{ji} \quad (3)$ $\bar{S} = \frac{\sum_{i=1}^n S_{i,in} + S_{i,out}}{2n} \quad (4)$ <p>Where, $S_{i,out}$ and $S_{i,in}$ are weighted in-degree and weighted out-degree respectively; N_i is the set of adjacent points of node v_i; w_{ij} is the weight of the directed edge from node v_i to node v_j, i.e. the number of tourists; \bar{S} is the average weighted degree of the whole network; n is the total number of nodes.</p>
Betweenness centrality	Reflects the degree of control (power) of the target node on other nodes in the network.	<p>Departing from the study of transportation networks, that commonly utilize the “shortest path length” in their calculations (Wang, Chen, Mu, & Zhang, 2020), we use the “maximum flow” between the nodes (Freeman, Borgatti, & White, 1991) for our directed-weighted network:</p> $B_i = \sum_{j \neq k} \sum_{l \neq i} \frac{m_{jk}(i)}{m_{jk}} \cdot j < k, \quad j \neq k \neq i \quad (5)$ <p>Where, m_{jk} is the maximum flow from node v_j to node v_k, i.e. the weight value of the path with the largest weight from node v_j to node v_k; $m_{jk}(i)$ is the maximum flow from node v_j to node v_k that passes through node v_i; n is the total number of nodes.</p>
Average shortest path length	Reflects the average distance between all nodes and the overall efficiency of the network.	$L = \frac{1}{C_n^2} \sum_{1 \leq i < j \leq n} d_{ij} \quad (6)$ <p>Where, d_{ij} represents the number of edges of the shortest path connecting two nodes v_i and v_j; When v_i and v_j are not connected, d_{ij} is regarded as infinite; n is the total number of nodes; C_n^2 is the total number of possible edges of the network composed of n nodes.</p>
Average clustering coefficient	Reflects the average connection tightness of all nodes in the network.	$\bar{C} = \frac{1}{n} \sum_{i=1}^n \frac{E_i}{C_{k_i}^2} \quad (7)$ <p>Where, E_i refers to the actual number of edges between k_i neighbor nodes of node v_i; $C_{k_i}^2$ refers to the total number of possible edges between k_i neighbor nodes of node v_i; n is the total number of nodes.</p>
Gravity center	Reflects the position where the strength of nodes in all directions is in balance.	$X = \frac{\sum_{i=1}^n s_i x_i}{\sum_{i=1}^n s_i}, Y = \frac{\sum_{i=1}^n s_i y_i}{\sum_{i=1}^n s_i} \quad (8)$ <p>Where, (X, Y) is the gravity center coordinate of the network; (x_i, y_i) is the coordinate of the ith node, expressed by the longitude and latitude of the attraction; s_i is the weight of the ith node, expressed by the weighted degree of the node (i.e., the sum of weighted in-degree and weighted out-degree); n is the total number of nodes.</p>

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \quad (9)$$

Where, m represents the number of edges in the network; A_{ij} is the adjacency matrix representing the weights of edges between node v_i and node v_j ; k_i is the sum of the weights of all edges connected with node v_i ; c_i represents the community number of node v_i ; if node v_i and node v_j are in the same community, the return value $\delta(c_i, c_j) = 1$, if not $\delta(c_i, c_j) = 0$.

Community detection based on modularity enables finding out the approximate optimal partition with the largest modularity of all the possible community partitions. Louvain algorithm (Blondel, Guillaume, Lambiotte, & Lefebvre, 2008) is widely considered as the best community detection method based on modularity (Lancichinetti & Fortunato, 2009). Recently, Lambiotte, Delvenne, and Barahona (2014) have improved the resolution limit of the algorithm by adding a “resolution” parameter allowing a sequential analysis. We used this improved method to detect communities in the complex network.

4. Results

4.1. Temporal characteristics

The starting point of our analysis was that we divided the geo-located travel blog data by month, and calculated the tourism intensity (i.e., the total number of visits by tourists to all attractions) of Chinese tourists in Nordic countries by each month (Fig. 4).

Fig. 4 shows that the tourism intensity of Chinese tourists in Nordic countries is relatively evenly distributed, except for September which is by far the most popular month for Chinese tourists to visit Nordic countries (the same result can be obtained from the statistics of the number of blogs in each month). The low value of the Annual Gini index (0.223), calculated by substituting the distribution of Fig. 4 into Eq. (1), verifies this observation. The result is inconsistent with the climate patterns of Nordic countries: weather-wise May to September should be the best season to travel to Nordic countries, since the temperatures are comfortable, the days are long and the nights are short during this period. Contrarily, the weather is cold from November to April. However, as shown in Fig. 4, tourism intensity is high also in February and December. Therefore, there is no obvious peak season of Chinese tourists. Rather, the temporal pattern of Chinese tourists in Nordic countries exhibits “no obvious off-season”.

There are some speculations on the cause of this even distribution of tourism intensity. The higher tourism intensity in December may be due to the fact that Christmas attracts Chinese tourists to the home of Father Christmas in Finnish Lapland. The higher tourism intensity in February may be due to China’s Spring Festival, but this is contrary to the lower tourism intensity in October, when another important festival, with one-week statutory holiday, China’s National Day, is celebrated. Therefore, it cannot be fully proved that festivals are the main cause of the even distribution. In order to further explore the causes of this even distribution, we explored the textual data of the travel blogs to find differences in Chinese tourists’ experiences throughout the year. First, the data in the cognition database was summarized by month and divided into twelve text sets. Second, “Chinese word segmentation” was carried out for these twelve sets of travel blog text data. The frequency of each word appearing in the text was counted. The resultant “word clouds” for each month are shown in Fig. 5. The size of the symbols in Fig. 5 represents the frequency of the words appearing in the travel blog text.

As shown in Fig. 5, the cognition of Chinese tourists in Nordic countries has obvious temporal heterogeneity: from October to March, “Aurora” is the most frequently used word, while from April to September, “Aurora” (almost) disappears in the word clouds. This shows that aurora (or northern lights) is an important factor for Chinese tourists to visit Nordic countries in the cold season (see also Cai, Ma, & Lee, 2020). Although aurora in Nordic countries may occur in any month of the year, the dark winter months provide the best viewing

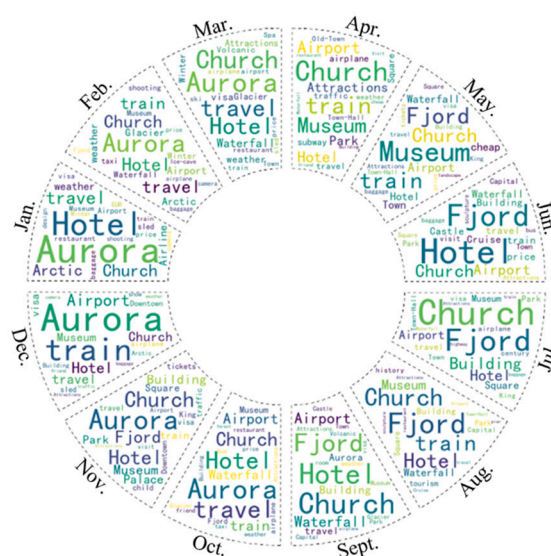
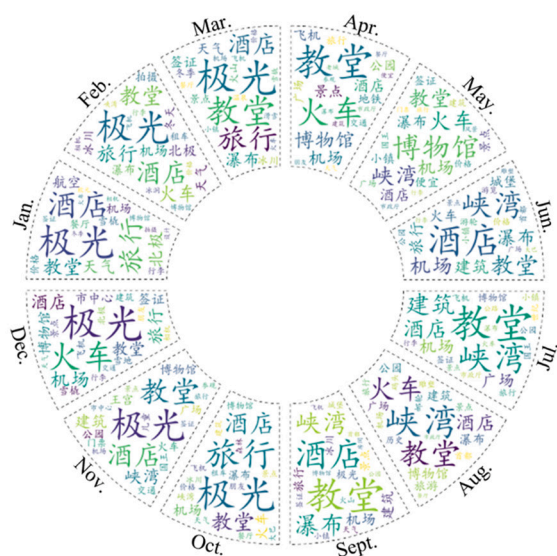
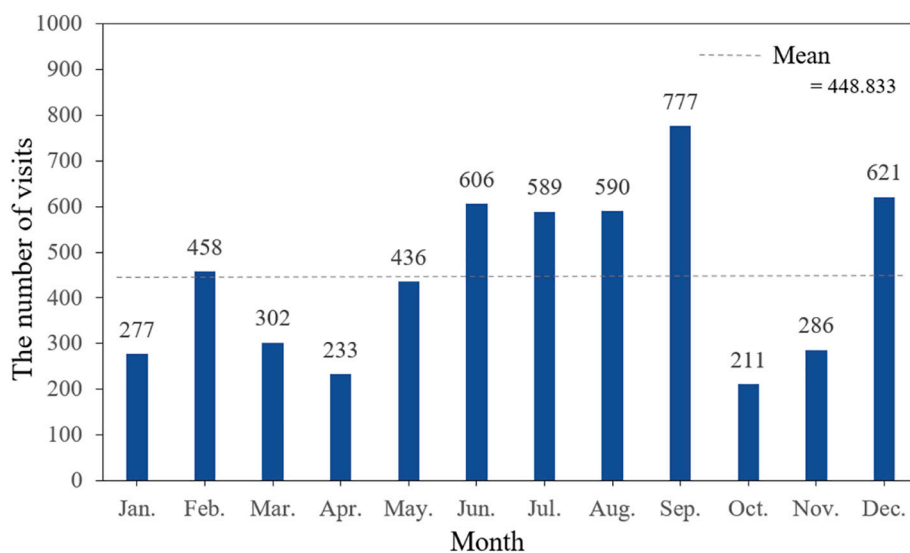
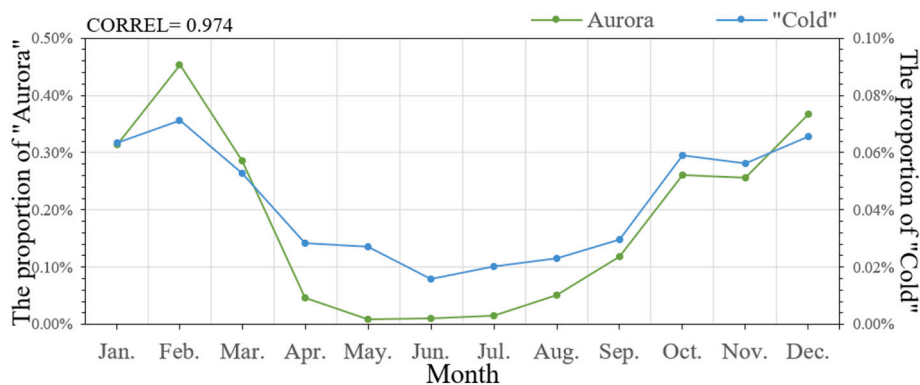


Fig. 5. The monthly variation of the “word clouds” of geo-located travel blog data.



experience for the phenomenon. In sum, the “aurora chasers” are an important factor in exploring the relatively even temporal distribution intensity of Chinese tourist in Nordic countries.

Based on the above, we selected the terms “Aurora” and “Cold” appearing in the travel blog textual data for further analysis. Since the two variables (“Aurora” and “Cold”) are normally distributed by K–S test, we used Pearson correlation coefficient to calculate the linear correlation between the two variables (Fig. 6). The calculated correlation coefficient between “Cold” and “Aurora” is 0.974 (p -value < 0.001). This very strong and statistically significant positive correlation further proves that many Chinese tourists do choose or expect to experience the aurora scenery when visiting Nordic countries during the cold season.

In conclusion, the distribution of tourism intensity of Chinese tourists in Nordic countries is relatively even throughout the year. The temporal heterogeneity of their travel cognition reveals the likely cause of this phenomenon: Chinese tourists’ pursuit of aurora scenery during the cold season.

4.2. Spatial characteristics

4.2.1. Network structure evaluation

In order to analyze the spatial characteristics of Chinese tourists’ behavior, we utilized the trajectory data to construct a tourist flow network of Chinese tourists between and within the five Nordic countries (Fig. 7).

The structural characteristic of the six tourist flow networks are shown in Table 2. Among the five national networks, Denmark’s and Iceland’s networks have the highest average weighted degrees (based on eq. 4), 13.776 and 13.941 respectively. This indicates that Chinese tourists move frequently between attractions within Denmark and Iceland (geographically the smallest Nordic countries). Finland (as a geographically much larger country) is the direct opposite of Denmark and Iceland: the average weighted degree of Finland’s network is only 9.094. The average weighted degree of Nordic countries network is 13.676. Therefore, it seems that Chinese tourists commonly cross borders between the Nordic countries and visit more than one of the five Nordic countries during their stay. To describe this cross-border travel behavior in greater detail, Fig. 8(a) and (b) show the distribution of the weighted in- and out-degrees (based on eq. 3) of the tourist flow network between the Nordic countries. The two figures show that Sweden seems to be the “hub” for cross-border travel of Chinese tourists in Nordic countries. This interpretation is further confirmed by the distribution of the betweenness centrality (based on eq. 5) in Fig. 8(c).

The opposite holds for Iceland’s network, which has the smallest average shortest path length (based on eq. 6) and the largest average clustering coefficient (based on eq. 7) out of the five Nordic countries. The small world effect (Watts & Strogatz, 1998) is, therefore, the most

obvious in the case of Iceland, indicating that Chinese tourists tend to regard Iceland as an independent travel destination when planning their trips. This is a logical result based on the geographical isolation of Iceland from the other Nordic countries. The overall network of Nordic countries has a relatively small average clustering coefficient and large average shortest path length. As such, generally the overall structure of the network is relatively “loose” due to the diversity of spatial behavior of Chinese tourists in Nordic countries.

Fig. 9 shows the distribution of the node degrees (based on eq. 2) of the six tourist flow networks and their power curve fitting. Among these tourist flow networks, except for Iceland’s network, the degree distribution of the networks basically satisfies the power-law distribution. That is the other networks exhibit strong heterogeneity and scale-free characteristics. Although the fitting curve of the degree distribution is affected by the number of network’s nodes, this effect can be ignored when comparing networks whose numbers of nodes are close (or in the same order of magnitude). Thus, the scale-free characteristics of five Nordic countries’ tourist flow networks can be quantitatively compared by the R^2 value (i.e. power fit degree). As shown in Fig. 9(a) to (e), Finland’s and Sweden’s networks exhibit the clearest scale-free characteristics, indicating that most Chinese tourists in these two countries are concentrated in only a few tourist attractions. Contrarily, Iceland’s and Norway’s networks exhibit the weakest scale-free characteristics, indicating that the spatial distribution of Chinese tourists between individual attractions in Iceland and Norway is relatively even. Therefore, there are no clear indications of concentrations of Chinese tourists only in certain (few) popular attractions. Overall, the Nordic countries’ network has strong scale-free characteristic, with R^2 value of 0.8432.

4.2.2. Community detection

As stated in Section 3.3.2, we used the improved Louvain algorithm to detect communities in the Nordic countries’ network. In order to avoid the shortcomings of a resolution limit, we initially set the resolution to 0 and then increased it sequentially by 0.1 for a continuous analysis. The resolutions and the resulting numbers of communities and modularity values (based on eq. 9) were subsequently recorded (Fig. 10).

As shown in Fig. 10, when the resolution is divided into six key values (or intervals), the tourist flow network of Chinese tourists in Nordic countries has distinctive community features: (1) the result of community detection has the highest value of modularity, up to 0.65, when the resolution is set to 1.1; (2) the number and distribution of communities is relatively stable in resolution intervals of 2–2.5, 2.6–3.9, 4–5, and 5.1–9.4; and (3) after the resolution is set to values greater than or equal to 9.5, the modularity value tends to 0, and, thus, the community detection results with high resolutions are no longer useful. Therefore, we selected the values of 1.1, 2.3, 3.3, 4.5, 5.4 and 10.5 as our

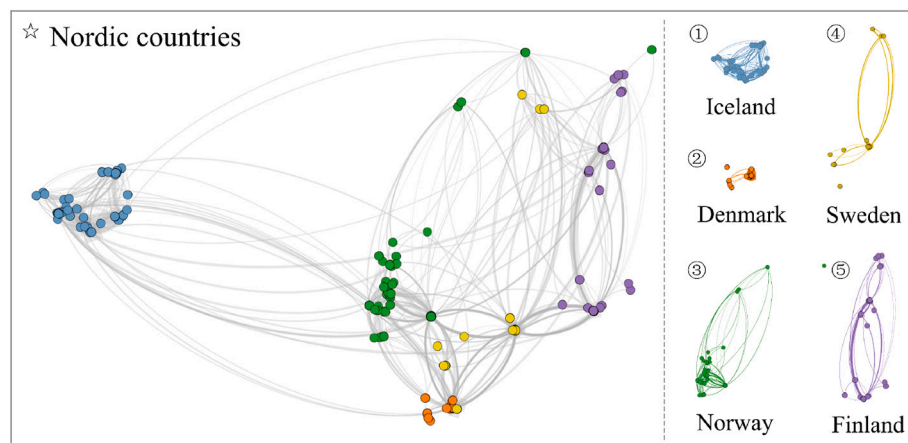
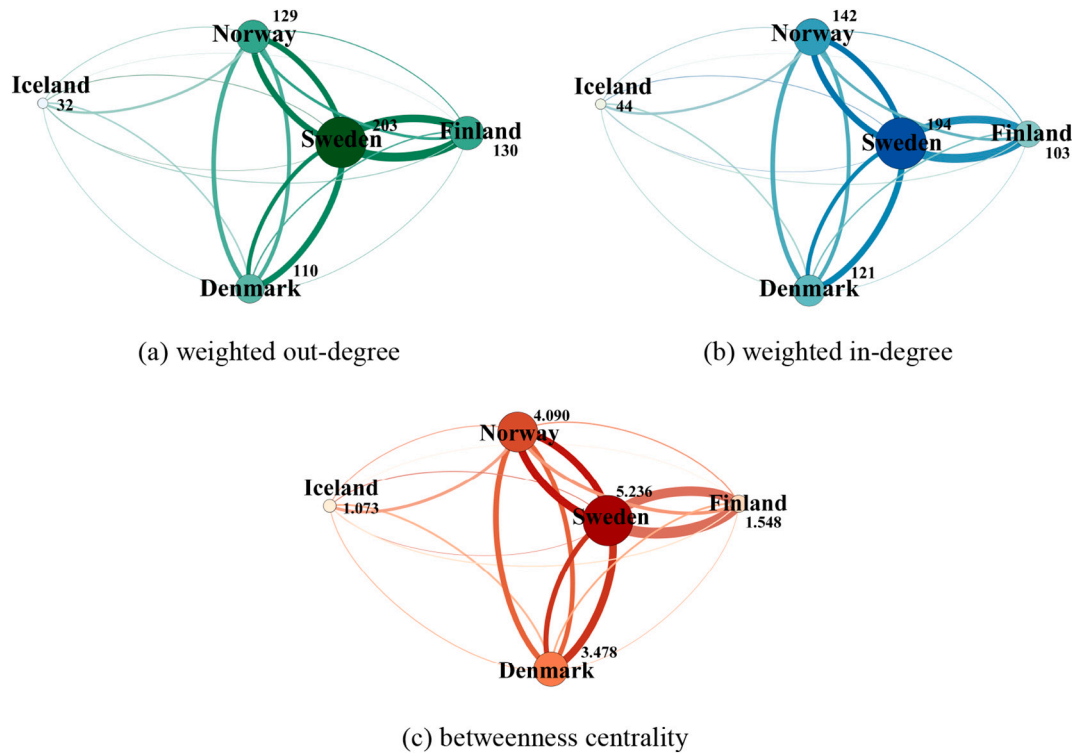


Fig. 7. The tourist flow networks between and within Nordic countries.

Table 2

The structural characteristics of the tourist flow networks of Chinese tourists in Nordic countries.

Network name	Number of nodes	Number of edges	Average weighted degree	Average shortest path length	Average clustering coefficient
Nordic countries	358	1540	13.676	3.469	0.328
Iceland	67	364	13.776	2.303	0.434
Denmark	85	316	13.941	2.686	0.343
Norway	81	292	10.444	2.678	0.320
Sweden	72	203	11.861	2.817	0.439
Finland	53	162	9.094	2.608	0.324

**Fig. 8.** The weighted degree and betweenness centrality distributions of the tourist flow network with countries as nodes.

key resolution values to carry out geographical visualization of the community detection results (Fig. 11).

As indicated in Fig. 11, Iceland has the highest community stability. The attractions in Iceland are all displayed as an independent community even with high resolutions, which is consistent with the significant small world effect of Iceland's network (as discussed in Section 4.2.1). This result gives further evidence that Chinese tourists in Nordic countries tend to regard Iceland as an independent travel destination. The second country with high community stability is Norway. Except for the observation that some of the attractions on the northern edge of Norway have always belonged to the communities of Sweden or Finland due to their geographical closeness to these countries, most of the attractions in Norway maintain high community independence when the resolution is less than five. Denmark has the lowest community stability, since it is affected by the communities in Norway and Sweden. This shows that Chinese tourists visiting Denmark do not commonly regard it as their only travel destination during their trip to the Nordic countries. In addition, the attractions in Sweden (except for Malmö in the southern "edge" of the country) and the attractions in Finland generally belong to the same community when the resolution is greater than two. This indicates that Chinese tourists commonly cross the border between Finland and Sweden and visit both countries (consistent with the results in Fig. 8) during their stay in the Nordic countries. Thus, Chinese tourists treat these two countries almost as one destination.

The above results are summarized as a schematic diagram in Fig. 12.

The numbers in the figure represent the community levels of each country. As the community independence of Iceland is significantly higher than that of the other Nordic countries, at the first level, the communities of Chinese tourists in Nordic countries can be roughly divided into two: "Western community" composed of Iceland and "Eastern community" composed of the remaining four Nordic countries. In addition to Iceland, Norway has a higher community independence and is less affected by nearby countries when the resolution changes. Sweden and Finland are often in the same detected community, which also has a higher community independence. In contrast, Denmark has the lowest community independence and its detected communities are affected by Sweden and Norway. Therefore, at the second level, the "Eastern community" can be subdivided into "Norwegian community", "Swedish-Finnish community", and "Danish community", which sort of "floats" between the other two Eastern communities. Finally, at the third level, the "Swedish-Finnish community" is sub-divided into two communities, Sweden and Finland, which are separated by a dotted line in the figure due to their close connection.

4.3. Spatio-temporal trends

We divided the network of Chinese tourists in Nordic countries into twelve time periods (according to months) and calculated the gravity center of the network for each month based on eq. (8) (Fig. 13).

Fig. 13 shows that the gravity center (concentrated in Norway and its

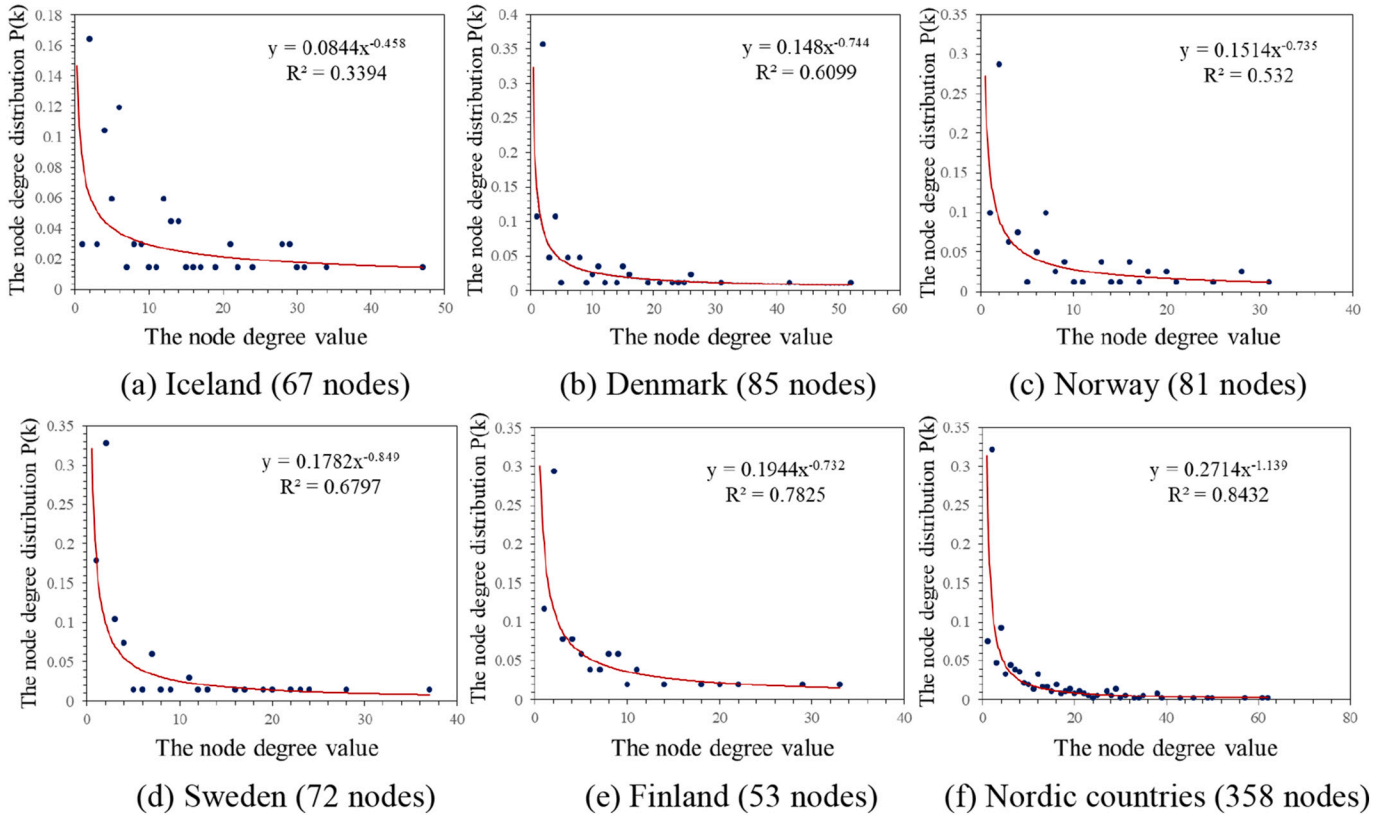


Fig. 9. The attractions' degree distribution curve of the tourist flow networks.

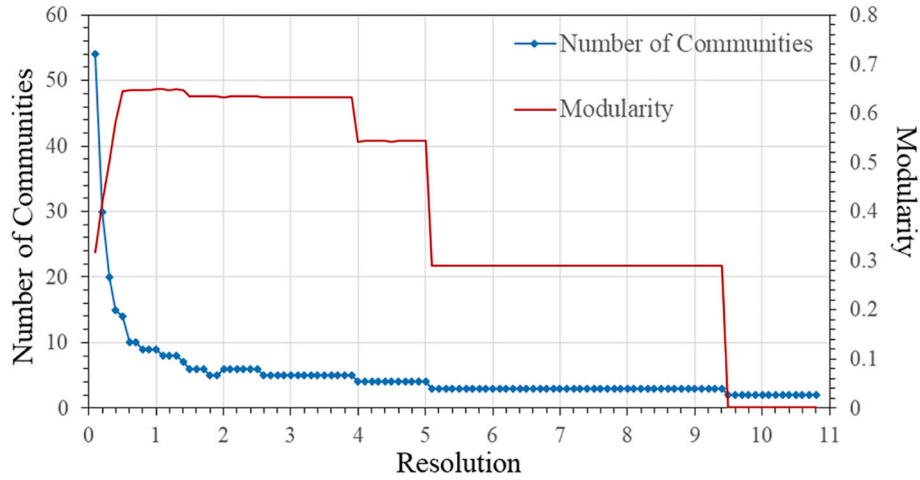


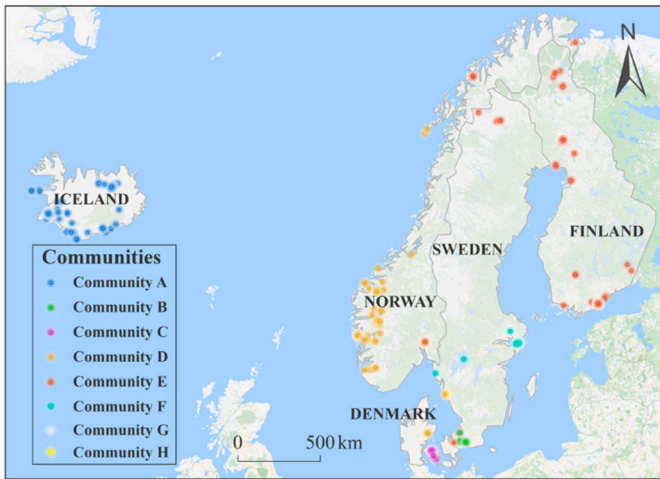
Fig. 10. The relative changes of resolution, number of communities and modularity based on a continuous community detection algorithm.

surrounding areas) of the network has a long cumulative moving (variation) distance (about 3900 km) during the year. The changes in the gravity center can be divided into different stages that support the findings presented earlier in this paper. During the coldest period (December to March) the gravity centers are at their northernmost position indicating that most Chinese tourists in Nordic countries at these months are “aurora chasers” visiting northern locations, where the changes of seeing the northern lights is the highest (in line with Section 4.1). There is also a clear tendency of Chinese tourists to visit the eastern parts of the Nordic countries in and around December (November to January) as seen in the change of the gravity center towards east. This is likely to be related to Finland marketing itself as the home of Father Christmas. From April to October, the change range of the gravity center

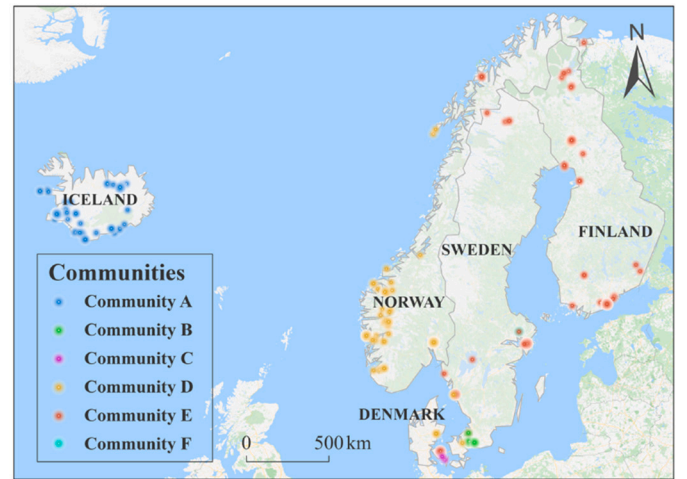
is relatively small, showing that Chinese tourists have a variety of destination choices, particularly in the western and southern parts of the Nordic countries, when they travel in Nordic countries during the warm season.

5. Discussion

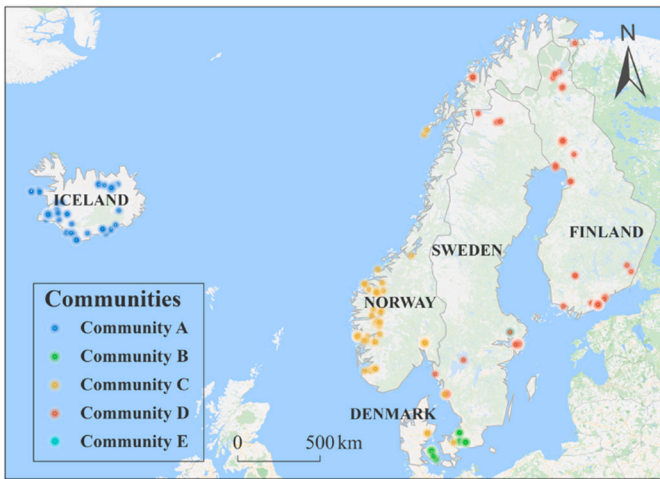
Our analysis of the temporal behavior of Chinese tourists in Nordic countries revealed that the distribution of tourism intensity is relatively even throughout the year. That is, the cold climate has no significant impact on the travel enthusiasm of Chinese tourists. China is one of the most important origin countries of tourists for Nordic countries. By making full use of the “no obvious off-season” feature and fully



(a) Resolution=1.1



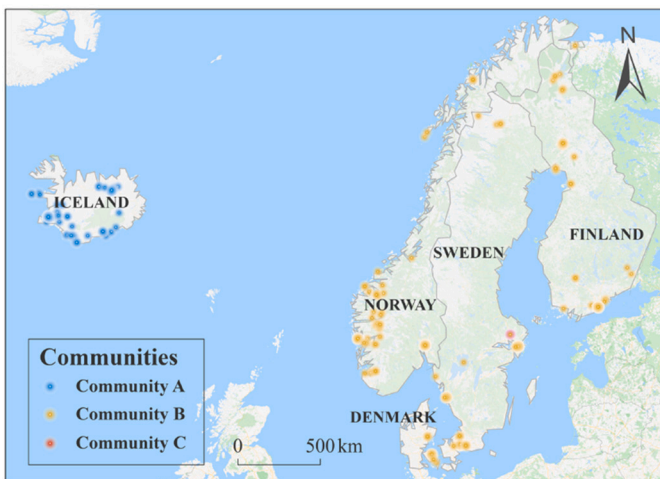
(b) Resolution=2.3



(c) Resolution=3.3



(d) Resolution=4.5



(e) Resolution=5.4



(f) Resolution=10.5

Fig. 11. Visualization of community detection results.



Fig. 12. The diagram of communities of Chinese tourists in Nordic countries.

Nordic countries are all members of the Schengen Agreement,² so it is convenient for Chinese tourists to travel within the five Nordic countries, resulting in frequent cross-border travel behavior. However, due to the differences in geographical environment of the different Nordic countries, the spatial distribution of Chinese tourists in the five Nordic countries is uneven. Among the five Nordic countries, Iceland is often regarded as an independent travel destination by Chinese tourists due to its distance from the other four Nordic countries, which leads to the strong small world effect of Iceland's network. The Iceland part of the Nordic countries network is also a relatively independent community. If the costs of traveling between Iceland and the other four countries could be reduced in the future, cross-border tourism between Iceland and the four other Nordic countries could be strengthened. This would effectively promote the tourism industries of all the five Nordic countries.

6. Conclusions

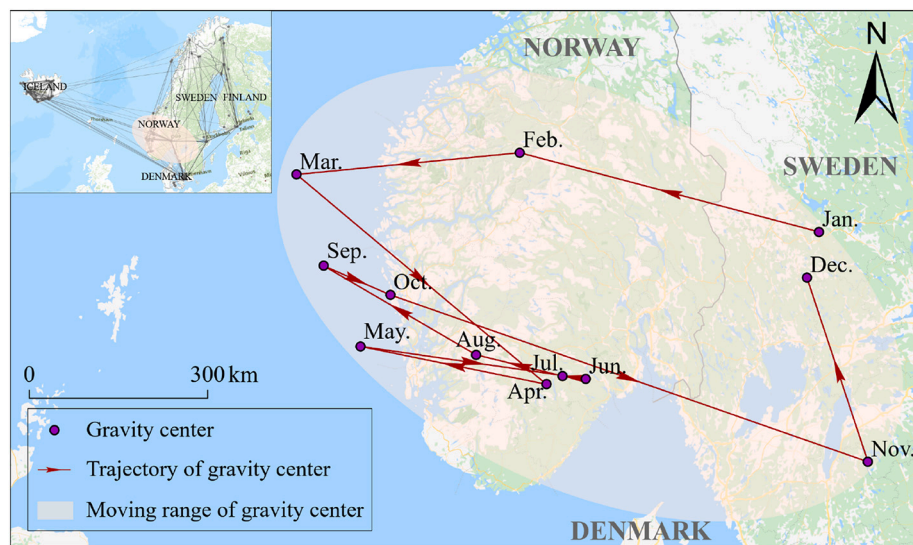


Fig. 13. The spatio-temporal distribution of the gravity center of Nordic countries network of Chinese tourists.

displaying the local winter tourism resources, such as aurora scenery or ice and snow activities in their tourism marketing, Nordic countries could potentially be able to narrow the tourism development gap between them and the most popular tourism destination countries in Europe. In fact, our analysis shows that Chinese tourists in Nordic countries often pursue the aurora scenery. This is an important reason for the even distribution of the tourism intensity throughout the year. Thus, aurora is one of the biggest tourism advantages of Nordic countries. However, best viewing season is often accompanied by the phenomenon of “long nights and short days” during the cold period. Yet, as stated by Jørgensen et al. (2018), Chinese tourists visiting Nordic countries are often experienced in traveling. Experienced tourists are usually passionate and willing to challenge themselves (even in cold climates). The movement of the gravity center of tourist flows further verifies and reflects the spatio-temporal trends of tourists' behavior (see also Mou & Zheng et al., 2020) revealing the seasonal and geographical patterns of Chinese tourists in Nordic countries. Thus, as shown by our analysis, the movement of the gravity center can effectively reflect the spatio-temporal trends of Chinese tourists and provide the basis for the tourism management departments of Nordic countries to formulate more targeted tourism development strategies per season.

This paper focused on the seasonal patterns and complex network effects of tourists' behavior, used geo-located travel blog data collected from Qunar.com to construct a database of tourists trajectories and cognition, and devised a detailed analysis of the spatio-temporal behavior of Chinese tourists in Nordic countries with the help of the Annual Gini index, Pearson correlation coefficient and complex network theory. The main conclusions can be summarized as follows:

- (1) The cold climate brought by seasonal changes does not prevent the enthusiasm of Chinese tourists to visit Nordic countries, which likely stems from the pursuit of aurora scenery by (experienced) Chinese tourists.
- (2) The travel behavior of Chinese tourists is characterized by obvious spatial heterogeneity. The constructed tourist flow network is typified by typical scale-free and small world effects and presents a complex community structure.
- (3) In the warm season, Chinese tourists choose a variety of destinations, while in the cold season, they tend to choose destinations with higher changes of experiencing the northern lights.

These results lead to concrete tourism policy suggestions. First,

² <https://www.schengenvisainfo.com/schengen-visa-countries-list/>

Nordic countries are advised to fully embrace the obvious attractiveness of Nordic countries for “aurora chasers” but also the apparent “no obvious off-season” characteristics of their tourism industry in subsequent tourism marketing and development. Second, promoting cross-border travel (via “country-hopping” tours, lowered travel costs, etc.) would spread the economic benefits of Chinese tourists more evenly between the five Nordic countries throughout the year and potentially “lure” these tourists to spend longer times in Nordic countries.

The presented methodology can naturally be applied also in other geographical contexts for the benefit of other countries and regions. The results presented in this paper are worthy of further exploration. These research avenues include, for example, adding emotional analysis to enhance the understanding of tourists’ cognition (Kang et al., 2019; Yan, Zhou, & Wu, 2018) or detecting spatial patterns of influencing factors (e. G. aurora scenery) to build motivation models of tourists (Wan et al., 2019). Moreover, a deeper exploration of the spatial structure of the Nordic countries as tourist destinations is also of great research value.

At the theoretical level, this paper decomposed the travel behavior of tourists into two elements, “mobility” and “cognition”, and combined these two elements to highlight tourists’ travel motivations. It provides a novel research perspective for the future study of tourists’ spatio-temporal behavior. In addition, this paper utilized the improved Louvain algorithm to detect tourism communities from dynamic resolution, for the first time, which enriches the study of the structure theory of tourist flow networks.

Although we do show that geo-located travel blog data can be used to describe the spatio-temporal behavior of tourists, the lack of representativeness of samples based on blog data is a constant cause for concern (Duggan, 2015). The users of Qunar.com are mainly “post-80s” and “post-90s” (i.e. people born between the years 1980 to 1999) with high educational levels and high income (IREsearch, 2016). The conclusions of this paper may, thus, be affected by this “skewness”. In addition, as a typical social media data source, the data bias of geo-located travel blogs should be given more attention in further studies. An ideal data bias evaluation of social media should be carried out from four perspectives, who, where, when, and what, but there is still a lack of solutions to fully address or quantify these perspectives (Yuan et al., 2019). The above shortcoming merits further empirical research and methodological evaluations. The obvious next step would be to integrate more travel data sources, such as other geo-located travel blogs from Ctrip (Ma, Wang, Xu, & Tai, 2018) or Qyer (Kaufmann et al., 2019), microblogs from Weibo (Zhang et al., 2020) or Twitter (Maeda, Yoshida, Toriumi, & Ohashi, 2018) and geo-tagged photos from Flickr (Su, Wan, Hu, & Cai, 2016) or Panoramio (Orsi & Geneletti, 2013), etc. into the analysis. This would allow us to achieve a more presentative picture of spatio-temporal behavior of (Chinese) tourists.

Acknowledgment

This research was supported in part by the National Natural Science Foundation of China (No. 41771476).

Declarations of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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